Telephone Triage: A Timely Data Source for Surveillance of Influenza-like Diseases

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We evaluated telephone triage (TT) data for public health early warning systems. TT data is electronically available and contains coded elements that include the demographics and description of a caller's medical complaints. In the study, we obtained emergency room TT data and after hours TT data from a commercial TT software and service company. We compared the timeliness of the TT data with influenza surveillance data from the Centers for Disease Control using the cross correlation function. Emergency room TT calls are one to five weeks ahead of surveillance data collected by the CDC.

INTRODUCTION

The threat of bioterrorism attacks and emerging infectious disease has generated interest in developing public health early warning systems capable of extreme timeliness of detection.[1] These approaches rely in part on the collection and analysis of data that are inherently earlier than conventional public health surveillance data. Examples of this type of data include absenteeism records,[2, 3] over the counter drug sales,[4, 5] patient chief complaints,[6, 7] real-time electronic laboratory reporting[8, 9] and 911 calls.[10]

Telephone triage (TT) is another data source of considerable interest. [11] Hospitals and healthcare systems use TT to direct patients to the appropriate medical resources.[12] For example, a parent whose child has a persistent cough could be directed to go to a pediatric walk-in clinic instead of an emergency department. Appropriate allocation of resources can lead to a significant reduction in costs[13, 14] and there is often a high degree of patient satisfaction with TT.[15] For these reasons, TT is becoming ubiquitous in today's managed care organizations.[16]

TT has several characteristics that make it a good candidate for early detection of disease outbreaks. TT occurs before patients visit an emergency room or a doctor's office, and thus TT data are likely to precede clinical data that arise from such clinical encounters. Also, TT can account for a large percentage of patient encounters—as much as 25% in internal medicine and even more in pediatrics.[15] Finally, modern TT call centers incorporate computer systems that track callers along with a coded description of their medical problem. Thus, TT can provide data electronically for surveillance and there is the capability for these TT systems to provide data in real time.

In this paper, we show how TT data can be used in public health early warning systems and evaluate the timeliness of two TT datasets when compared to conventional influenza surveillance data.

METHODS

TT Datasets

We obtained two TT datasets from a healthcare call center services and software company. One dataset came from an emergency room telephone triage facility (we refer to that dataset as ER-TT) that serves 10 hospitals in a major city and the other dataset came from an after-hours telephone triage facility for a group of physician offices in a single state (referred to as AH-TT). The two datasets were from two geographically distant areas. Each dataset contained 13 months of data, from September 1, 2001 to August 31, 2002, The ER-TT dataset contained 21,304 records and the AH-TT dataset contained 18,135 records. Each record in the datasets consisted of 10 elements:

1. Start date/time of initial call
2. Acuity: acute or non-acute
3. Inclination of the caller: There were 12 unique reasons why a call could be made. Examples are call physician, research, and 911.
4. Disposition assigned to the caller by the nurse: There were 23 unique dispositions. Examples are home care, see MD within 24 hours, call PCP within 24 hours, and ER immediately.
5. Call outcome: This element uses the same 23 possible values used in the disposition.
6. Primary symptoms in free-text: Examples are "stomach bug - 6 loose bowel movements throughout the day" and "feels hot and some pain in throat."
7. Five digit home zip code
8. Age
9. Gender
10. Treatment guideline used: There were 380 unique guidelines used in the datasets. A single guideline chosen by the triage nurse is recorded for each call. Examples include diarrhea, earache, breathing difficulty, vomiting, and asthma attack.

In the ER-TT dataset callers were encouraged to call TT before going to the emergency room. In the AH-TT dataset callers were routed to TT when physician offices were closed. When a person contacts the call center, a nurse records the *basic demographics* of the patient as well as the *symptoms* of the patient into the call center computer system. The nurse determines why the person is calling (the *inclination)* and if the caller has an *acute medical emergency*. Then, the nurse uses a standard *guideline* or protocol to interview the person and determine what the person should do (the *disposition)*. Finally, the nurse may make a followup-call to determine if the person followed the nurse's advice (the *call outcome*).

Guideline-to-Syndrome Mapping

It is usually necessary in public health surveillance to define syndromic categories as a group of health-related codes that are likely to be used for a patient presenting with that particular syndrome.[6, 17, 18] In the case of TT guidelines, there is likely to be considerable variation in the way that callers with a particular disease present themselves to a TT nurse and the selection of a guideline by the nurse For this reason, we mapped guidelines into syndromes.

We categorized the 380 unique guidelines found in the datasets into a set of mutually exclusive categories that corresponded to syndromes of public health interest. We included a guideline in a syndrome category if the guideline could be used for a patient presenting with symptoms of interest to public health officials. We based the syndromes on syndrome definitions previously developed by the US Department of Defense, the CDC and the Utah Department of Health.

Gold Standard Determination of Influenza Outbreak

We chose the 2001-2002 outbreak of the disease influenza to evaluate the timeliness of TT data relative to conventional surveillance data. Influenza surveillance data is readily available from the Centers for Disease Control (CDC) and because of antigenic drifts or shifts in the influenza virus there are usually yearly outbreaks available for study. We obtained the following influenza surveillance data from the CDC website at http://www.cdc.gov/ncidod/diseases/flu/:

1. Weekly state epidemiologist reports of estimated influenza activity. (CDC-SI)
2. The weekly regional *number* of influenza-like-illness[1] (ILI) cases from the U.S. Influenza Sentinel Physicians Surveillance Network. (CDC-RI)
3. The weekly regional number of positive influenza tests (CDC-RC)

The datasets we obtained were specific to the geographic coverage of each TT dataset.

We wanted to use state as well as regional influenza surveillance data. While the *number* of ILI cases is available regionally, only estimated levels of influenza activity (item number one in the preceding list) are available. Subjective assessments of influenza activity each week are reported as one of four values:

- *No Activity*: No cases of influenza or ILI reported.
- *Sporadic*: Cases of influenza or ILI are reported, but reports of outbreaks in places such as schools, nursing homes, and other institutional settings have not been received.
- *Regional*: Outbreaks of influenza or ILI are occurring in geographic areas containing less that 50% of the state's population. A geographic area could be a city, county, or district.
- *Widespread:* Outbreaks are occurring in geographic areas representing more than 50% of the state's population.

In order to include state influenza activity data in our quantitative analyses, we assigned an ordinal value to each of the estimated flu activity levels: "No activity" was assigned a value of 0, "sporadic" was assigned a value of 1, "regional" was assigned a value of 2, and "widespread" was assigned a value of 3. We accounted for missing flu activity data by interpolation, using the average of the two nearest weeks.

Classifying TT Calls as Influenza Calls

We defined an influenza call as a TT call coded with a guideline that we had categorized as being either respiratory or constitutional. We aggregated calls into weekly counts to match the weekly aggregation of influenza surveillance data.

Cross Correlation Metric

We used the cross-correlation function (CCF)[19] to measure the time latency between TT and conventional influenza surveillance. In particular, we computed the cross-correlation function for the weekly counts of influenza calls from the ER-TT dataset and the AH-TT datasets with the state (CDC-SI) and regional (CDC-RI and CDC-RC) influenza surveillance data. Prior to computing the cross correlation function, we normalized each of the time-series to the number of standard deviations from the mean to satisfy the assumption of cross correlation analysis that the time series being compared are normalized to the same scale.

This type of analysis produces a correlation number over a range of possible time latencies between time series. We used the time latency (a.k.a. lag) at which the correlation number was maximized as our measure of timeliness, a method first used by Tsui et al.[19]

A lag of zero would indicate that TT data are no more or less timely that conventional surveillance data. A lag less than zero would indicate that TT data are more timely that conventional surveillance data. A lag greater than zero would indicate that TT data are less timely than conventional surveillance data.

RESULTS

Guideline-to-Syndrome Mapping

Of the 380 guidelines used in the ER-TT and AH-TT datasets, we assigned 69 guidelines to eight syndromic categories—gastrointestinal, respiratory, constitutional, hemorrhagic, rash, lymphadenopathy, botulinic, and neurologic. We further subdivided these primary categories into smaller categories to distinguish syndromes with and without fever, the disease location, and individual symptoms like cough that are important public health indicators (although we did not use these subdivisions in the meas-

[1] The CDC defines *influenza like illness* as fever (temperature of >100°F) plus either a cough or a sore throat.

urements of timeliness with the correlation function, we provide them in Figure 1 for other researchers). The final influenza guideline set, comprised eighteen respiratory guidelines and four constitutional guidelines.

TT vs. Regional Influenza Surveillance Data

On inspection, the TT and regional influenza surveillance data (CDC-RI and CDC-RC) have similar temporal patterns (See Figure 2 and Figure 3). Cross correlation analysis (See Figure 4 and Table 1) shows that ER-TT occurs earlier than CDC-RI (has a maximal correlation at a negative time lag) and AH-TT occurs later than regional influenza surveillance data.

TT vs. State Influenza Surveillance Data

ER-TT and CDC-SI have very similar temporal patterns. AH-TT and CDC-SI are moderately similar. Cross correlation analysis shows that ER-TT occurs earlier than CDC-SI and AH-TT occurs later than CDC-SI.

DISCUSSION

In this paper we attempt to show how TT data can be used in public health early warning systems and test the hypothesis that TT data are more timely than current influenza surveillance data. We used the 2001-2002 influenza outbreak and cross correlation analysis to test this hypothesis.

Is TT a timely data source?

Our analysis shows that ER-TT can be a timely data source for monitoring influenza outbreaks. This study shows the limitations in using cross correlation analysis alone to evaluate the timeliness of secondary data (data collected for other reasons) in public health surveillance. According to the cross correlation analysis, the after hours TT data comes after the conventional influenza surveillance data. The graphs of the data, however, show that *there is a gradual increase in AH-TT calls several weeks before there is a steep increase but the regional influenza surveillance data do not show this characteristic*.

One possible reason for the late peak in influenza calls to AH-TT is that patients might be more likely to wait until the doctor's office is open instead of talking to the after hours triage service. This would lead to a large percentage of patients with influenza that are not captured. Only when patients are experiencing severe influenza symptoms at the height of the influenza outbreak do they call the AH-TT center.

There are also limitations in the using state influenza activity in this analysis. The state influenza activity level is based on *estimates* of influenza activity in the state. Is the appearance of multiple peaks of influenza activity in the AH-TT state due to poor reporting to the state health department or a real phenomenom?

How can public health use TT data?

TT data are collected primarily to maintain a record of the interaction between a caller and a nurse, and are not collected for public health surveillance purposes. The TT datasets we obtained nevertheless contain two types of information useful for public health—the demographics of the person requiring medical assistance and descriptions of that person's symptoms. The descriptions were available in coded and free text versions. Although natural language processing tools are available to interpret free-text medical data, they often require a large amount of training data in order to be effective. Therefore, we specifically focused on the coded guideline of the call as a proxy of the caller's symptoms for this initial study.

In order to use the TT data to monitor an outbreak like influenza, we defined a set of syndromes. The syndromes are mutually exclusive to eliminate double counting of records when leaf categories are combined into higher-level categories (recall that each phone call is associated with exactly one guidleline). The syndrome categories are hierarchal and sufficiently granular to allow for a high degree of modeling flexibility. For example, if an epidemiologist wanted to compute the incidence of all TT calls associated with fever, she could "build" a syndromic definition with the leaves of hierarchy pertaining to fever. Although we only used the respiratory and constitutional syndrome categories in this evaluation, we show the entire set for completeness.

In this evaluation we focused on a single element of TT data—the coded guideline. We note that the data contain other elements—acuity of the call, inclination, age, and gender—that are also potentially useful to public health. For example, public health might want to know the weekly incidence of acute fever in callers between 10 and 20 years old who are male.

TT Limitations and Future Work

One limitation of TT for public health early warning systems is that TT is not ubiquitous. Although market projections anticipate steady growth of TT services[14] they have not achieved widespread use except in areas with large managed care organizations. Also, many of the treatment guideline sets are proprietary in nature and are distributed by multiple TT software vendors. This makes it more difficult for TT to be universally incorporated into public health early warning systems unless methods to map the free-text primary symptoms of the caller to syndromes are used (i.e., natural language processing).

This paper suggests that ER-TT data are more timely than currently collected influenza surveillance data. Future work must confirm or refute this pilot observation using multiple years of TT data so that confident estimates of the sensitivity and specificity of influenza detection using TT data can be made. Data from other known disease outbreaks should be obtained to evaluate the potential of TT data to providing early warning of disease outbreaks other than influenza. Finally, work should be done to evaluate how the other elements in the data, particularly demographic and spatial information, can be used to identify smaller outbreaks of disease.

CONCLUSION

For detection of influenza-like illnesses, TT data is a promising data source for use in public health surveillance.

TT has several favorable characteristics including electronic availability, coded data elements, and timeliness.

TABLES AND FIGURES

- **All Guidelines in Dataset**
  - **Of Interest to Public Health**
    - **Gastrointestinal**
      - **Gastrointestinal-Vomiting (3)**
      - **Gastrointestinal-Diarrhea (2)**
      - **Gastrointestinal-Other (7)**
    - **Respiratory**
      - **Respiratory-Influenza (2)**
        - *Influenza*
        - *Influenza (Adult)*
      - **Respiratory-Upper (13)**
        - *Colds (Adult)*
        - *Colds*
        - *Congestion*
        - *Sinus Infection Follow-Up Call*
        - *Sore Throat*
        - *Strep Throat Infection Follow-Up Call*
        - *Throat Culture Follow-Up*
      - **Respiratory-Lower (3)**
        - *Bronchiolitis Follow-Up Call*
        - *Breathing Difficulty (Adult)*
        - *Breathing Difficulty, Severe*
        - *Asthma Attack*
        - *Asthma Attack (Adult)*
        - *Wheezing*
      - **Respiratory-Cough (3)**
        - *Cough*
        - *Cough, Acute Productive (Adult)*
        - *Cough, Acute 0n-Productive (Adult)*
    - **Constitutional**
      - **Constitutional-Fever (2)**
        - *Fever (Adult)*
        - *Fever*
      - **Constitutional-Other (1)**
        - *Weakness*
      - **Constitutional-Crying Child (1)**
        - *Crying Child*
    - **Hemorrhagic (7)**
    - **Rash**
      - **Rash-Localized (7)**
      - **Rash-Diffuse (7)**
      - **Rash-Location Unspecified (2)**
    - **Lymphadenopathy (1)**
    - **Botulinic (1)**
    - **Neurologic**
      - **Neurologic-Seizure (1)**
      - **Neurologic-Other (7)**
      - **Neurologic-Seizure w/Fever (1)**
      - **Neurologic-Seizure w/o Fever (1)**
  - **Other (311)**

Figure 1. Syndromic categories for TT data. The number of guidelines in each category is given in parentheses. The guideline descriptions for the respiratory and constitutional categories are shown in italics.

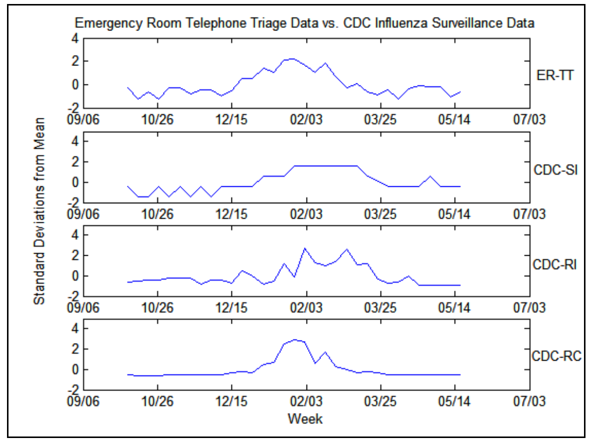

Figure 2. Emergency room TT and CDC influenza surveillance. Each time-series plots weekly counts. *ER-TT*=emergency room TT influenza calls; *CDC-SI*=state influenza activity from the CDC; *CDC-RI*=regional influenza like illness cases from the CDC; and *CDC-RC*=regional positive cultures from the CDC.

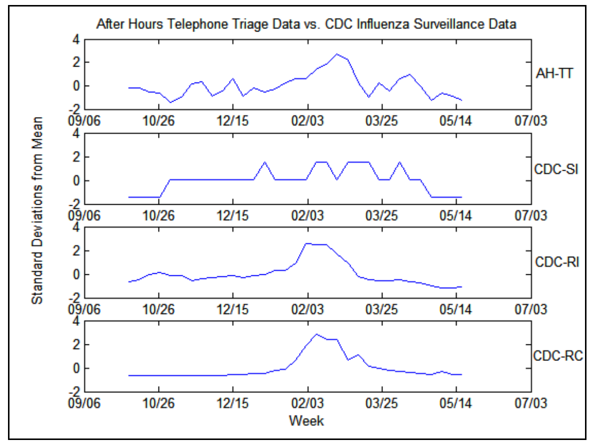

Figure 3. After hours TT and CDC influenza surveillance data. Each time-series plots weekly counts. *AH-TT*=after hours TT influenza calls. CDC data label abbreviations are the same as in Figure 2.

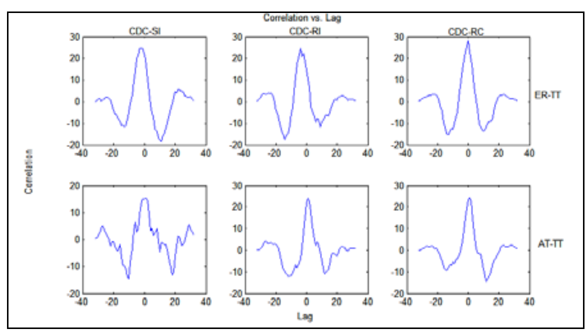

Figure 4. Cross correlation analysis of TT data and CDC influenza surveillance data. Data label abbreviations are the same as in Figures 2 and 3.

Table 1. Time lag in weeks at maximum correlation between TT data and CDC influenza data. Data label abbreviations are the same as in Figures 2 and 3. Correlation is shown in parentheses (maximum possible correlation is 32.00).

	CDC-SI	CDC-RI	CDC-RC
ER-TT	-1(24.74)	-4(24.66)	0(28.04)
AH-TT	1(15.18)	1(23.97)	1(24.33)

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